

Predictive or Oblivious: A Comparative Study of Routing Strategies for Wireless Mesh Networks Under Uncertain Demand

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Abstract—Traffic routing plays a critical role in determining the performance of a wireless mesh network. To investigate the best solution, existing work proposes to formulate the mesh network routing problem as an optimization problem. In this problem formulation, traffic demand is usually implicitly assumed as static and known *a priori*. Contradictorily, recent studies of wireless network traces show that the traffic demand, even being aggregated at access points, is highly dynamic and hard to estimate. Thus, in order to apply the optimization-based routing solution in practice, one must take into account the dynamic and uncertain nature of wireless traffic demand.

There are two basic approaches to address the traffic uncertainty in network routing: (1) predictive routing which infers the traffic demand with maximum possibility based in its history and optimizes the routing strategy based on the predicted traffic demand and (2) oblivious routing which considers all the possible traffic demands and selects the routing strategy where the worst-case network performance could be optimized. This paper conducts a systematic comparison study of these two approaches based on the extensive simulation study over a variety of network and traffic scenarios. It identifies the key factors of the network topology and traffic profile that affect the performance of each routing strategy and provides guidelines towards the strategy selection in mesh network routing under uncertain traffic demands.

I. INTRODUCTION

Wireless mesh networks (*e.g.*, [1], [2]) which now offer a rapid and inexpensive solution to last-mile broadband Internet access, are attracting ever greater attention and widespread deployment. A wireless mesh network is composed of local access points and wireless mesh routers which form an organic backbone structure which forwards traffic between mobile clients and the Internet.

Traffic routing plays a critical role in determining the performance of a wireless mesh network. Thus it has attracted extensive recent research. The key challenges come from the scarce wireless channel resource, high dynamic link quality, and the uncertain traffic demands. The proposed approaches address these challenges in different ways. On one end of the spectrum are the heuristic algorithms (*e.g.*, [3]–[6]). Although many of them are adaptive to the dynamic environments of wireless networks, these algorithms lack the theoretical foundation to analyze how well the network performs globally (*e.g.*, whether the scarce channel resource is shared in an optimal and fair fashion). On the other end of the spectrum, there are theoretical studies that formulate mesh network routing as optimization problems (*e.g.*, [7], [8]). The routing algorithms derived from these optimization formulations can

usually claim analytical properties such as resource utilization optimality and throughput fairness. In these optimization frameworks, traffic demand is usually implicitly assumed as static and known *a priori*. Recent studies of wireless network traces [9], however, show that the traffic demand, even being aggregated at access points, is highly dynamic and hard to estimate. Such observations have significantly challenged the practicability of the existing optimization-based routing solutions in wireless mesh networks.

One natural approach to address the traffic uncertainty in network routing is predictive routing [10], [11], which infers the traffic demand with maximum possibility based on history and optimizes the routing strategy for the predicted traffic demand. Underlying predictive routing is the assumption that past behavior is a good indicator of the future. The quality of a predictive algorithm is therefore tightly related to the traffic erraticity.

However, considering the high degree of uncertainty in wireless mesh networks, the following questions are still open issues: (1) how much benefit we are able to gain from the predictive routing; (2) under what circumstance does predictive routing perform the competitively. To answer these questions, this paper contrasts the predictive routing with a radically different routing strategy – *oblivious routing*. Oblivious routing makes no assumption on traffic demand. Instead, it considers all the possible traffic demands and selects the routing strategy where the worst-case network performance is optimized.

This paper conducts a systematic comparison study of these two approaches based on the extensive simulation study over a variety of network and traffic scenarios. It identifies the key factors of the network topology and traffic profile that affect the performance of each routing strategy and provides guidelines towards the strategy selection in mesh network routing under uncertain traffic demands. To evaluate the performance of these two algorithms under realistic wireless networking environment, we conduct a trace-driven simulation study. In particular, we derive the traffic demand for the local access points of our simulated wireless mesh network based on the traffic traces collected at Dartmouth College campus wireless networks. Our simulation results demonstrate that predictive routing performs better under consistent traffic demand compared to highly variable demand, as determined by our erraticity metric. Furthermore, oblivious routing, being a stateless routing, is unaffected by erraticity. The performance of both algorithms is sensitive to demand and topology,

suggesting that the optimal choice for deployment should be based on local parameters.

The original contributions of this paper are threefold. First, it provides evidence for the competitive performance of oblivious routing in highly-variable traffic networks. Secondly, it conducts a detailed simulation of predictive and oblivious routing to confirm the intuition for their respective most favorable conditions, in terms of traffic demand. Finally, we offer a metric that quantifies the erraticity of multidimensional demand over time, such as multiple access points fluctuating independently.

The remainder of this paper is organized as follows. Sec. II presents the network and system model. Sec. III reviews the optimal mesh network routing strategy and the traffic prediction method, and shows how these two could be integrated into predictive mesh network strategy. Sec. IV presents the oblivious mesh network routing formulation and algorithm. Sec. V presents our simulation study. Finally, Sec. VI discusses the related work and Sec. VII concludes the paper.

II. MODEL

A. Network and Interference Model

In a multi-hop wireless mesh network, local access points aggregate and forward traffic for the mobile clients which are associated with them. They communicate with each other and with the stationary wireless routers to form a multi-hop *backbone* network, which forwards the user traffic to the Internet gateways. We use $w \in W$ to denote the set of gateways in the network and $s \in S$ to denote the set of local access points that generate traffic in the network. Local access points, gateways and mesh routers are collectively called mesh nodes and denoted by the set V .

In a wireless network, packet transmissions are subject to location-dependent interference. Here we consider the *protocol model* presented in [12]. We assume that all mesh nodes have the uniform transmission range denoted by R_T . Usually the interference range is larger than its transmission range, which is denoted as $R_I = (1 + \Delta)R_T$, where $\Delta \geq 0$ is a constant. For simplicity, in this paper we assume that each node is equipped with one radio interface which operates on the same wireless channel as others. Let $r(u, v)$ be the distance between two nodes u and v ($u, v \in V$). In the protocol model, packet transmission from node u to v is successful, if and only if (1) the distance between these two nodes $r(u, v)$ satisfies $r(u, v) \leq R_T$; (2) any other node $x \in V$ within the interference range of the receiving node v , i.e., $r(x, v) \leq R_I$, is not transmitting. If node u can transmit to v directly, they form an edge $e = (u, v)$. We assume that the maximum data rate that can be transmitted along an edge is the same for all edges, and denote it as c (also called channel capacity). Let E be the set of all edges. We say two edges e, e' interfere with each other, if they can not transmit simultaneously based on the protocol model. Further we define *interference set* $I(e)$ which contains the edges that interfere with edge e and e itself.

Finally, we introduce a virtual node w^* to represent the Internet. w^* is connected to each gateway with a virtual

edge $e^* = (w^*, w), w \in W$. Further, let $E' = E \cup \{e^*\}$ and $V' = V \cup \{w^*\}$. For simplicity, we assume that the link capacity in the Internet is much larger than the wireless channel capacity, and thus the bottleneck always appears in the wireless mesh network. Under this assumption, the virtual edges could be regarded as having unlimited capacity, and they do not interfere with any of the wireless transmissions.

B. Traffic Model and Schedulability

This paper studies the routing strategies for wireless mesh *backbone* networks. Thus it only considers the aggregated traffic between the local access points and the Internet gateways. Here we call the aggregated traffic in (or out) a local access point a *flow* and denote it as $f \in F$, where F is the set of all aggregated flows. All flows will take w^* as their source (or destination). We denote the traffic demand of flow f as d_f and use vector $\mathbf{d} = (d_f, f \in F)$ to denote the demand vector consisting of all flow demands.

Now we proceed to study the constraint of the flow rates. Let $\mathbf{y} = (y(e), e \in E)$ denote the edge rate vector, where $y(e)$ is the aggregated flow rate along e . Edge rate vector \mathbf{y} is said to be schedulable, if there exists a stable schedule that ensures every packet transmission with a bounded delay. Essentially, the constraint of the flow rates is defined by the schedulable region of the edge rate vector \mathbf{y} .

The edge rate schedulability problem has been studied in several existing works, which lead to different models [13]–[15]. In this paper, we adopt the model in [14], which is also extended in [7] for multi-radio, multi-channel mesh network. In particular, [14] presents a sufficient condition under which an edge scheduling algorithm is given to achieve stability with bounded and fast approximation of an ideal schedule. [7] presents a scheme that can adjust the flow routes and scale the flow rates to yield a feasible routing and channel assignment. Based on these results, we have the following claim as a sufficient condition for schedulability.

Claim 1. (*Sufficient Condition of Schedulability*) The edge rate vector \mathbf{y} is schedulable if the following condition is satisfied:

$$\forall e \in E, \sum_{e' \in I(e)} y(e') \leq c \quad (1)$$

III. PREDICTIVE MESH NETWORK ROUTING

This section reviews the predictive mesh network routing strategy. It first presents the problem formulation of optimal mesh network routing under fixed traffic demand, then shows how predictive mesh network routing could infer the traffic demand with maximum possibility based on a time-series model and optimize the routes based on the predicted traffic.

A. Optimal Mesh Network Routing

The existing works on optimal multihop wireless network routing [7], [8], [13] usually formulate it as a throughput optimization problem which maximizes the flow throughput, while satisfying the fairness constraints. In this formulation,

traffic demand is fixed and reflected as the flow weight in the fairness constraints. Recall that $f \in F$ is the aggregated traffic flow between the local access points and the virtual gateway (*i.e.*, Internet) and $\mathbf{d} = (d_f, f \in F)$ is the demand vector consisting of all flow demands. Consider the fairness constraint that, for each flow f , its throughput being routed is in proportion to its demand d_f . The goal of throughput maximization routing is to maximize λ (so called *scaling factor*) where at least $\lambda \cdot d_f$ amount of throughput can be routed for flow f .

To balance the traffic load, flow f could be routed over multiple paths, let \mathcal{P}_f be the set of unicast paths that could route flow f , and $x_f(P)$ be the rate of flow f over path $P \in \mathcal{P}_f$. Obviously the aggregated flow rate y_e along edge $e \in E$ is given by $y_e = \sum_{f:P \in \mathcal{P}_f \& e \in P} x_f(P)$, which is the sum of the flow rates that are routed through paths P passing edge e . Based on the sufficient condition of schedulability in Claim 1 (Eq.(1)), we have that

$$\sum_{e' \in I_e} \sum_{f:P \in \mathcal{P}_f \& e' \in P} x_f(P) \leq c \quad (2)$$

To simplify the above equation, we define $A_{eP} = |I_e \cap P|$ as the number of wireless links path P passes in the interference set I_e . The throughput optimization routing with fairness constraint is then formulated as the following linear programming (LP) problem:

$$\mathbf{P}_T : \quad \text{maximize} \quad \lambda \quad (3)$$

$$\text{subject to} \quad \sum_{P \in \mathcal{P}_f} x_f(P) \geq \lambda \cdot d_f, \forall f \in F \quad (4)$$

$$\sum_{f \in F} \sum_{P \in \mathcal{P}_f} x_f(P) A_{eP} \leq c, \forall e \in E \quad (5)$$

$$\lambda \geq 0, x_f(P) \geq 0, \forall f \in F, \forall P \in \mathcal{P}_f \quad (6)$$

In this problem, the optimization objective is to maximize λ , such that at least $\lambda \cdot d_f$ units of data can be routed for each aggregated flow f with demand d_f . Inequality (4) enforces fairness by requiring that the comparative ratio of traffic routed for different flows satisfies the comparative ratio of their demands. Inequality (5) enforces the capacity constraint by requiring the traffic aggregation of all flows passing wireless link $e \in E$ satisfy the sufficient condition of schedulability. This problem formulation follows the classical maximum concurrent flow problem.

While the above throughput maximization routing problem formulation is widely used in designing optimal mesh network routing strategies under known demands, it is not suitable to study the routing performance under dynamic and uncertain traffic demand. Here we consider a formulation based on another routing performance metric – network *congestion* (or *utilization*). In Internet, *link utilization* is commonly used for traffic engineering [16], whose objective is to minimize the utilization at the most congested link under given traffic demand. However, link utilization can not be straightforwardly

applied to multihop wireless networks, such as mesh backbone network, as a metric of routing performance due to the location-dependent interference. In what follows, we define the *network congestion based on the utilization of the interference set* as the routing performance metric and outline the relation between the formulation of the throughput optimization problem and the congestion minimization problem.

Let $x'_f(P)$ be the rate of flow f on path P under traffic demand d_f . It is obvious that $\sum_{P \in \mathcal{P}_f} x'_f(P) = d_f$. The traffic being routed within the interference set I_e is then given by $\sum_{f \in F} \sum_{P \in \mathcal{P}_f} x'_f(P) A_{eP}$. Formally, the *congestion* of an interference set I_e is defined as its *utilization* (*i.e.*, the ratio between its load and the channel capacity) and denote it as θ_e :

$$\theta_e = \frac{\sum_{f \in F} \sum_{P \in \mathcal{P}_f} x'_f(P) A_{eP}}{c} \quad (7)$$

Further, the *network congestion* is defined as the maximum congestion among all the interference sets, *i.e.*,

$$\theta = \max_{e \in E} \theta_e \quad (8)$$

The network congestion minimization routing problem is then formulated as follows:

$$\mathbf{P}_C : \quad \text{minimize} \quad \theta \quad (9)$$

$$\text{subject to} \quad \sum_{P \in \mathcal{P}_f} x'_f(P) \geq d_f, \forall f \in F \quad (10)$$

$$\sum_{f \in F} \sum_{P \in \mathcal{P}_f} x'_f(P) A_{eP} \leq c \cdot \theta, \forall e \in E \quad (11)$$

$$\theta \geq 0, x'_f(P) \geq 0, \forall f \in F, \forall P \in \mathcal{P}_f \quad (12)$$

To reveal the relation between \mathbf{P}_T and \mathbf{P}_C , we let $\theta = \frac{1}{\lambda}$ and $x'_f(p) = \frac{x_f(p)}{\lambda}$. Problem \mathbf{P}_C is then transformed to:

$$\mathbf{P}'_C : \quad \text{minimize} \quad \frac{1}{\lambda} \quad (13)$$

$$\text{subject to} \quad \frac{1}{\lambda} \sum_{P \in \mathcal{P}_f} x_f(P) \geq d_f, \forall f \in F \quad (14)$$

$$\frac{1}{\lambda} \sum_{f \in F} \sum_{P \in \mathcal{P}_f} x_f(P) A_{eP} \leq c \cdot \theta, \forall e \in E \quad (15)$$

$$\lambda \geq 0, x_f(P) \geq 0, \forall f \in F, \forall P \in \mathcal{P}_f \quad (16)$$

which is obviously equivalent to the throughput optimization problem \mathbf{P}_T .

If the demand vector \mathbf{d} is known, both problem \mathbf{P}_T and \mathbf{P}_C could be solved by a LP-solver such as [17], [18]. To reduce the complexity for practical use, the work of [10] also presents a fully polynomial time approximation algorithm for problem \mathbf{P}_T , which finds an ϵ -approximate solution.

B. Traffic Prediction

Under dynamic traffic conditions, however, the traffic demand vector \mathbf{d} usually can not be known a priori. To address

this problem, the predictive mesh network routing estimates the traffic demand based on the analysis of its dynamic behavior. Our recent work [11] presents a traffic prediction method and two predictive mesh routing algorithms which integrate the predicted traffic with the routing optimization. In this paper, we will adopt the Mean-Value Prediction Routing (MVPR) routing strategy for comparison study. In what follows, we briefly review this predictive routing strategy.

In this method, a traffic model is first built using time-series analysis based on the traffic traces (*snmp* log) collected at the campus wireless LAN network of Dartmouth College in Spring 2002 [19]. It is argued that the access points of a wireless LAN serve a similar role and thus exhibit similar behavior as the local access points of a wireless mesh network. To illustrate the modeling procedure, we choose one of the access points (ResBldg97AP3) as an example, whose its incoming traffic series is plotted in Fig. 1.

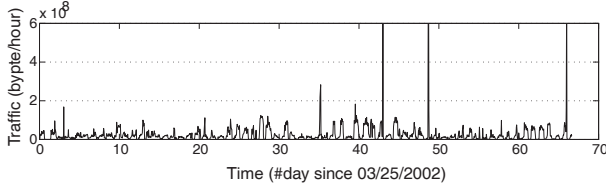


Fig. 1. Incoming Traffic Time Series of ResBldg97AP3 (March 25, 12am, 2002 - June 9, 11pm, 2002 EST).

The first step of the analysis is to identify and remove the daily and weekly cyclic patterns in the time series. Formally, let $x(t)$ denote the *raw traffic series*. The moving average of this series can be estimated based on the same time of the day: $\bar{x}(t) = \sum_{i=1}^W x(t - 24 \times i) / W$, where W is the size of moving window. After removing the cyclic effect from the raw data, the *adjusted traffic series* $z(t)$ is derived as $z(t) = x(t) - \bar{x}(t)$. The adjusted traffic series contains the short-term (a few hours) traffic correlations which can be modelled as an autoregressive process.

$$z(t) = \beta_1 z(t-1) + \beta_2 z(t-2) + \dots + \beta_K z(t-K) + \epsilon \quad (17)$$

where K is the process order. To apply this model for prediction, the parameters of this process need to be estimated. Given N observations z_1, z_2, \dots, z_N , the parameters β_1, \dots, β_K are estimated via least squares by minimizing:

$$\sum_{t=K+1}^N [z(t) - \beta_1 z(t-1) - \dots - \beta_K z(t-K)]^2 \quad (18)$$

Based on the estimated parameters, the adjusted traffic prediction $\hat{z}(t)$ is given as

$$\hat{z}(t) = \beta_1 z(t-1) + \beta_2 z(t-2) + \dots + \beta_K z(t-K) \quad (19)$$

Fig. 2 plots the predicted series for the adjusted traffic, in comparison with its raw data and the fitted traffic series over the interval [720, 779].

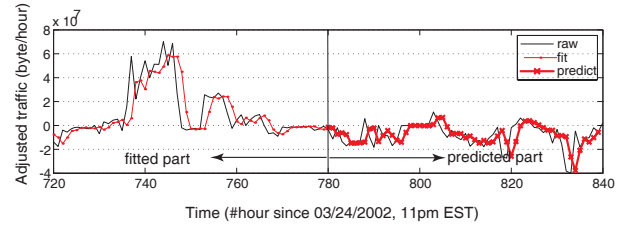


Fig. 2. Adjusted Traffic and Its Prediction

The traffic demand \hat{x} is then predicted as follows:

$$\hat{x}(t) = [\bar{x}(t) + \hat{z}(t)]^+ \quad (20)$$

where $[x]^+ = \max\{0, x\}$.

Finally, Mean-Value Prediction Routing (MVPR) routing strategy will take the predicted traffic demand \hat{x}^1 of a flow f (i.e., the aggregated traffic in/out the corresponding local access point) as the demand input d_f to the LP problem \mathbf{P}_C and derive its routing strategy.

IV. OBLIVIOUS MESH NETWORK ROUTING

In contrast to the predictive routing which establishes traffic models based on time-series analysis and optimizes towards the traffic demands with maximum possibility, oblivious routing makes no assumptions on the traffic model, rather it will consider all traffic demand possibilities and optimizes towards the worst-case scenario. To formally study oblivious routing strategy, we need a performance metric that could characterize the worst-case congestion under all possible traffic demand.

(1) Routing:

First, let's examine the formal description of *routing*, which specifies how traffic of each flow is distributed across the network. In the previous formulation (\mathbf{P}_C), a routing is characterized through the traffic load distribution along different paths (i.e., $x'_f(P)$). This description of a routing depends on the traffic demand of each flow. When we have to consider all possible traffic demands, it becomes infeasible. In fact, a routing strategy could be modelled independently of the traffic demand, which is the core of the oblivious routing problem formulation.

Formally, we define a *routing* by the fraction of each flow that is routed along each edge $e \in E'$. We use $\phi_f(e)$ to denote the fraction of demand of flow f that is routed on the edge $e \in E'$. Thus, a routing could be specified by the set $\phi = \{\phi_f(e), f \in F, e \in E'\}$. Recall that the demand of flow $f \in F$ is denoted by d_f . Therefore, the amount of traffic demand of f that needs to be routed over e in routing ϕ , denoted by $y'_f(e)$, is given as follows:

$$y'_f(e) = d_f \cdot \phi_f(e) \quad (21)$$

Thus the *congestion* θ_e of an *interference set* $I(e)$ is given by

¹Actually, this is the mean-value of the predicted traffic demand, which itself is a random variable. For details, please refer to [11].

$$\theta_e = \sum_{e' \in I(e)} \sum_{f \in F} \frac{y'_f(e')}{c} = \sum_{e' \in I(e)} \sum_{f \in F} \frac{d_f \cdot \phi_f(e')}{c} \quad (22)$$

We further use $\theta(\phi, \mathbf{d}) = \max_{e \in E} \theta_e(\phi, \mathbf{d})$ to denote the network congestion under a certain routing ϕ and traffic demand vector \mathbf{d} .

(2) *Oblivious Performance Ratio*:

Now we proceed to study the performance metric that could characterize a “good” routing solution under all possible traffic demands. We start with the *optimal routing* $\phi^{opt}(\mathbf{d})$ for a certain demand vector \mathbf{d} , which would give the minimum congestion under this demand, *i.e.*,

$$\theta^{opt}(\mathbf{d}) = \min_{\phi} \theta(\phi, \mathbf{d}) \quad (23)$$

Now we define the *performance ratio* $\gamma(\phi, \mathbf{d})$ of a given routing ϕ on a given demand vector \mathbf{d} as the ratio between the network congestion under the routing ϕ and the minimum congestion under the optimal routing, *i.e.*,

$$\gamma(\phi, \mathbf{d}) = \frac{\theta(\phi, \mathbf{d})}{\theta^{opt}(\mathbf{d})} \quad (24)$$

Performance ratio γ measures how far ϕ is from being optimal on the demand \mathbf{d} . Now we extend the definition of performance ratio to handle uncertain traffic demand. Let \mathbf{D} be a set of traffic demand vectors. Then the performance ratio of a routing ϕ on \mathbf{D} is defined as the worst-case performance ratio for all demands in \mathbf{D} , *i.e.*,

$$\gamma(\phi, \mathbf{D}) = \max_{\mathbf{d} \in \mathbf{D}} \gamma(\phi, \mathbf{d}) \quad (25)$$

A routing ϕ^{opt} is optimal for the traffic demand set \mathbf{D} if and only if

$$\phi^{opt} = \arg \min_{\phi} \gamma(\phi, \mathbf{D}) \quad (26)$$

which means ϕ^{opt} minimizes the performance ratio under the worst-case scenario. When the set \mathbf{D} includes all possible demand vectors \mathbf{d} , we refer to the performance ratio as the *oblivious performance ratio*. The oblivious performance ratio is the worst performance ratio a routing obtains with respect to all possible demand vectors. To study the optimal routing strategy under uncertain traffic demand, we are interested in the *optimal oblivious routing* problem which finds the routing that minimizes the *oblivious performance ratio*. We call this minimum value the *optimal oblivious performance ratio*.

It is worth noting that the performance ratio γ is invariant to scaling. Thus to simplify the problem, we only consider traffic demand vectors \mathbf{D} that satisfy $\theta^{opt}(\mathbf{d}) = 1$, instead of considering all possible traffic vectors. In this case,

$$\gamma(\phi, \mathbf{D}) = \max_{\mathbf{d} \in \mathbf{D}} \theta(\phi, \mathbf{d}) \quad (27)$$

Thus the goal of oblivious routing is given by

$$\min_{\phi} \max_{\theta^{opt}(\mathbf{d})=1} \theta(\phi, \mathbf{d}) \quad (28)$$

(3) *Flow Conservation*

Traffic into and out of a mesh node must be conserved. In \mathbf{P}_C , a *path representation* of the routing is being used ($x'_f(P)$), which implicitly formulates the flow conservation. Here, since we use an *edge representation* of the routing ($\phi_f(e)$), the flow conservation has to be explicitly formulated. In particular, for the node $v \in V'$ that only relays for flow f (*i.e.*, neither source or destination), we have the following relations:

$$\forall f \in F, \sum_{e=(u,v)} y'_f(e) - \sum_{e=(v,u)} y'_f(e) = 0 \quad (29)$$

if v is a relay of f

If v is the source node of flow f , then we have

$$\forall f \in F, \sum_{e=(u,v)} y'_f(e) - \sum_{e=(v,u)} y'_f(e) = -d_f \quad (30)$$

if v is the source node of f

Summarizing the above discussions, the *oblivious mesh network routing* problem is formulated as follows.

$$\mathbf{P}_O : \quad (31)$$

$$\text{minimize } \theta \quad (32)$$

$$\text{subject to } \sum_{e' \in I(e)} \sum_{f \in F} \frac{y'_f(e')}{c} \leq \theta, \forall e \in E \quad (33)$$

$$\sum_{e=(u,v)} y'_f(e) - \sum_{e=(v,u)} y'_f(e) = 0 \quad (34)$$

$$\forall f \in F, \forall v \in V', \text{ if } v \text{ is a relay of } f$$

$$\sum_{e=(u,v)} y'_f(e) - \sum_{e=(v,u)} y'_f(e) = -d_f \quad (35)$$

$$\forall f \in F, \forall v \in V', \text{ if } v \text{ is the source node of } f$$

$$\forall f \in F, \forall e \in E, y'_f(e) = d_f \cdot \phi_f(e) \geq 0 \quad (36)$$

$$\theta \geq 0, \forall \mathbf{d} \text{ with } \theta^{opt}(\mathbf{d}) = 1 \quad (37)$$

Different from \mathbf{P}_C , the oblivious mesh routing problem \mathbf{P}_O cannot be solved directly, because it is taken over all demand vectors, and $\theta^{opt}(\mathbf{d})$ is an embedded maximization in the minimization problem.

Here we use a similar method as in [20], which provides a LP formulation of the oblivious routing problem. The key insight is to look at the dual problem of the slave LPs of the original oblivious routing problem. Given a routing $\phi_f(e)$, the constraints (33) can be tested by solving, for each interference set $I(e)$, the following “slave LP”, and testing if the objective is $\leq \theta$ or not.

V. SIMULATION STUDY

$$\begin{aligned} \max \quad & \sum_{e' \in I(e)} \sum_{f \in F} \frac{d_f \cdot \phi_f(e')}{c} & (38) \\ \text{subject to} \quad & \phi_f(e) \text{ is a routing;} & (39) \\ & \text{constraints (34),(35)} & (40) \\ & \sum_{e' \in I(e)} \sum_{f \in F} y_f(e') \leq c & (41) \end{aligned}$$

In the dual formulation, we first introduce interference set weights $\pi_e(e')$ for every pair of interference sets e, e' . Each π variable can be thought of as a dual multiplier on the capacity constraint. There are three essential properties shown in **Theorem 1**.

Theorem 1. A routing ϕ has oblivious ratio $\leq \theta$ if and only if there exist weights $\pi_e(e')$, for every pair of interference set $I(e), I(e'), e, e' \in E$, such that

$$\begin{aligned} \text{P1} \quad & \forall e, e' \in E, \sum_{e' \in E} c \cdot \pi_e(e') \leq \theta; \\ \text{P2} \quad & \forall \text{ paths } h, \forall f \in F, \forall e \in E \\ & \sum_{e' \in I(e)} \phi_f(e') \leq c \cdot \sum_{a \in E} \pi_e(a) |I(a) \cap h| \\ \text{P3} \quad & \forall \text{ interference sets } I_e, I_{e'}, \pi_e(e') \geq 0 \end{aligned}$$

Since the number of paths between any two nodes grows exponentially with the size of the network (in P2). In order to retain polynomial solvability, we introduce variable $\zeta_e(u, v)$ for each edge e and node pair u and v , which is the length of the shortest path from u to v based on interference set weights $\pi_e(e')$. The introduction of these variables allows us to replace the exponential number of constraints in P2 with a polynomial number of constraints. Summarizing the above discussions, the LP formulation of problem P_O is given as follows:

$$\begin{aligned} \mathbf{P}_{LP} : \\ \text{minimize} \quad & \theta & (42) \\ & \phi \text{ is a routing} & (42) \\ & \forall e, e' \in E : \sum_{e' \in E} c \cdot \pi_e(e') \leq \theta & (43) \\ & \forall e \in E, \forall f : u \rightarrow v \in F : & (44) \\ & \sum_{e' \in I(e)} \phi_f(e') / c \leq \zeta_e(u, v) \\ & \forall u \in V, \forall a = (v, w) \in E, \\ & \sum_{a' \in I(a)} \pi_e(a') + \zeta_e(u, v) - \zeta_e(u, w) \geq 0 \\ & \forall u \in V, \zeta_e(u, u) = 0 \\ & \forall u, v \in V, \zeta_e(u, v) \geq 0 \\ & \forall e, e' \in E, \pi_e(e') \geq 0 & (45) \end{aligned}$$

In the above formulation, Eq. (43) can be explained by property P1. Property P2 and the shortest interference set paths account for Eq. (44), and finally property P3 appears at Eq. (45). The problem \mathbf{P}_{LP} is a single polynomial-size LP instance, which can be solved with any LP solver. Our choice of LP solver was *lp_solve* [18], an open source Mixed Integer Linear Programming (MILP) solver.

A. Performance Overview

In this section, we simulate the predictive and oblivious routing strategies over a variety of mesh network setups. Our goal is to evaluate and compare their performance and identify the key factors that impact the performance. Two other routing strategies, namely oracle routing and shortest-path routing, are used as the baseline strategies for comparison. We describe the routing strategies that are evaluated in the simulation study as follows.

- *Oracle Routing (OR)*. In this strategy, the traffic demand is known *a priori*. It runs every hour based on the up-to-date traffic demand and returns the optimal set of routes. As a result, no other routing strategies can outperform *OR*, and we used it to provide a performance upper bound.
- *Shortest-Path Routing (SPR)*. This strategy is agnostic of traffic demand, and returns a fixed routing solution purely based on the shortest distance (number of hops) from each mesh node to the gateway. Many mesh network routing heuristics resemble the shortest-path routing strategy. We evaluate this strategy to quantitatively contrast the advantage of routing strategies which explicitly consider traffic uncertainty.
- *Predictive Routing (PR)*. This strategy attempts to adjust to changing the traffic demand. Future demand is estimated based on the historical data every hour based on the traffic prediction method presented in Sec. III-B.
- *Oblivious Routing (OBR)*. This strategy is oblivious to the traffic demands. It considers all possible traffic demands that may be imposed on the network and finds a routing that optimizes the worst-case congestion using the algorithm presented in Sec. IV.

It is worth noting that the *SPR* and *OBR* will compute the traffic routes only once and use them during the entire simulation time, while the *OR* and *PR* need to compute and update the routes every hour.

To realistically simulate the traffic demand at each LAP, we employ the traces collected in the campus wireless LAN network. The network traces used in this work are collected in Spring 2002 at Dartmouth College and provided by CRAW-DAD [19]. By analyzing the *snmp* log trace at each access point, we are able to derive its 1108-hour incoming and outgoing traffic volume beginning 12:00AM, March 25, 2002 EST. We select the access points from the Dartmouth campus wireless LAN and assign their traffic traces to the LAPs in our simulation. The traffic assignment is given in Table I in one of the random topologies as shown in Fig. 3.

We experiment with the above routing strategies along the time range [108, 1108], a 1000-hour period excerpted from the trace². Note that all the simulation results presented in this section use 108 as the zero point.

²Note that the beginning of the trace [0, 107] is used as training data, thus it is not included in the simulation result.

AP	31AP3	34AP5	55AP4	57AP2	62AP3	62AP4	82AP4	94AP1	94AP3	94AP8
Node ID	22	18	57	5	55	20	53	3	56	27

TABLE I
TRAFFIC ASSIGNMENT FROM TRACE FILE

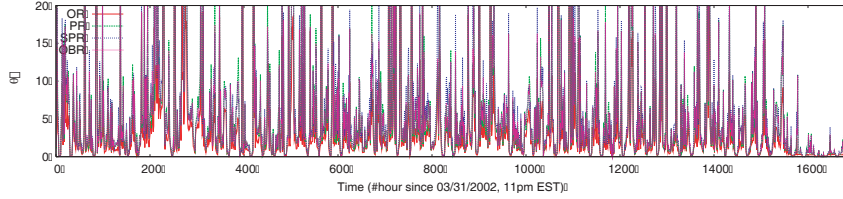


Fig. 4. Overview of All Strategies

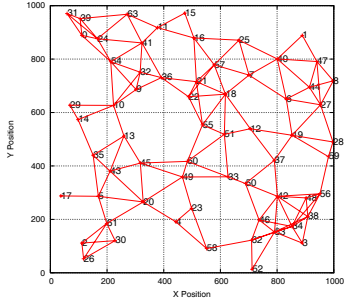


Fig. 3. Mesh Network Topology

We start by presenting the congestion achieved by all strategies during the entire 1000-hour simulation period. As seen in Fig. 4, *OR* constantly achieves the minimum worst-case congestion among others, due to its unrealistic capability to know the actual traffic demand. We note that the burstiness of θ applies to all strategies including *OR*. This observation comes from the burstiness of the traffic load in the *snmp* log trace, which is caused by the insufficient level of traffic multiplexing at wireless local access points.

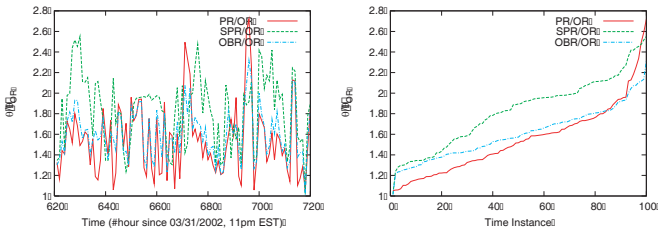


Fig. 5. (a) Congestion Ratio ($\frac{\theta}{\theta_{OR}}$) (b) Sorted View

To filter out the noise caused by traffic burstiness, in Fig. 5(a), we normalize θ achieved by other strategies by the same value of *OR*. Since *OR* always achieves the minimum θ among others, this ratio will end up at least 1. Also we take a close-up look during the hour range [190, 290]. Here, *PR*, *SPR*, and *OBR* achieve less than 2 times of the optimal congestion in most cases. The above observations get clearer when we sort out the normalized congestion ratio for the

three strategies in Fig. 5(b). It is clear that both *PR* and *OBR* which integrate the traffic prediction with the optimal routing outperform the *SPR* strategy which is agnostic about the traffic demand. Further, *PR* achieves lower congestion than *OBR* for many time points due to more comprehensive representation of the traffic demand estimation. However, in other cases (less than 10% of the time), the worst-case congestion of *PR* is substantially higher than *OBR*. This problem can be mostly attributed to the fundamental inaccuracy of traffic prediction.

B. Impact of Network Topology

We investigate the performance of *PR* and *OBR* in a representative random topologies with Internet gateways near the perimeter. For a more complete picture, we investigate cases with 2 gateways and with 4 gateways. Each of these topologies has a total of 64 nodes, including 10 access points receiving traffic from mobile clients, the gateways, and the remaining nodes forwarding traffic on behalf of the Internet and the access points. The points are distributed at random over a simulation square 1000m on the side, with an interference range of 155m. For simplicity, the transmission range is equal to the interference range.

In both the 4-gateway and the 2-gateway scenarios, we run *PR*, *OBR* and *SPR* using the demand data from the Dartmouth trace. Fig. 6 plots the congestion ratios of *PR* over *SPR* and *OBR* over *SPR*. In both pictures, *OBR* and *PR* outperform *SPR* in more than 50% of the cases. During the time when they are inferior to *SPR*, the worst-case ratio is bounded by 2. Also when we increase the number of gateways from 2 to 4, both ratios decrease. Obviously, *SPR* takes advantage of this topology change, due to the fact that more gateways will diversify the shortest paths from access points to nearest gateways, and also shrink the lengths of the paths.

To study the impact of path length to our strategies, we create 7 random topologies whose shortest paths from access points to the nearest gateways have different hop counts. The value ranges from 2.5 to 5.5. In Fig. 7, *OBR*, *PR*, and *SPR* consistently deliver better congestion ratio when the hop count decreases. Among the three, *SPR* has the worst congestion ratio except in the case when the average hop count is 4. Moreover, the performance of *SPR* worsens at an

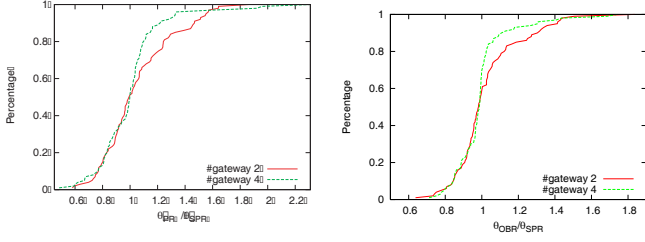


Fig. 6. (a) CDF of Congestion Ratio ($\frac{\theta_{PR}}{\theta_{SPR}}$) (b) CDF of Congestion Ratio ($\frac{\theta_{OBR}}{\theta_{SPR}}$)

accelerated speed when the average hop count further grows, coinciding with what is observed in Fig. 6. Comparatively, the congestion ratio of *OBR* and *PR* degrades gracefully, with *OBR* consistently outperforming *PR* by less than 0.1.

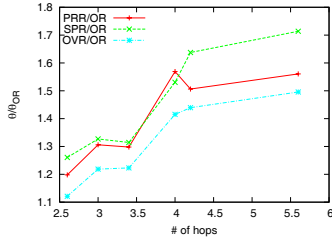


Fig. 7. Congestion Ratio ($\frac{\theta}{\theta_{OR}}$) vs. # hops

Fig. 6 and 7 collectively demonstrate that *OBR* and *PR* are more advantageous than the simple shortest path routing scheme in large and complicated topologies with long paths from access points to gateways.

C. Impact of Traffic Demand

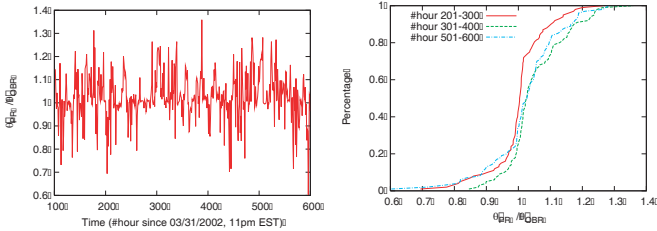


Fig. 8. (a) Congestion Ratio ($\frac{\theta_{PR}}{\theta_{OBR}}$) (b) CDF of Congestion Ratio

We now study the impact of traffic dynamics on the performance of our routing strategies. We first define a metric to characterize the dynamic behavior of the wireless traffic. Our goal is to measure the variation in a demand across a set of LAPs over time. We require that a single metric encompass the individual variations and be a useful predictor of the performance of the predictive routing strategy. We define the *traffic erraticity* at time t to be

$$e_t = \frac{\sum_{a \in AP} |a_{t-1} - a_t|}{\sum_{a \in AP} \max(a_{t-1}, a_t)}$$

There are several favorable properties of e_t as follows:

- This metric is sensitive to any perturbation in any of the LAPs' demands.
- $0 \leq e_t \leq 1$. In other words, the metric occupies an intuitive and fixed range.
- e_t is insensitive to scaling in demand. This is necessary since scaling does not affect performance ratios
- e_t is sensitive to changes in an LAP's demand in proportion to that LAP's total contribution to the demand.
- e_t is symmetric. We would expect that for any demands sets d_a, d_b , the two transitions $d_a \rightarrow d_b$ and $d_b \rightarrow d_a$ would be equally erratic.

To characterize the correlation between routing performance and erraticity, we plot e_t compared to θ_{PR}/θ_{SPR} in Fig. 9(a) and $\theta_{OBR}/\theta_{SPR}$ in Fig. 9(b). The Fig. 9(a) data fits a trendline with $R^2 = 0.115$, proving that predictive performance is influenced by the traffic erraticity. Figure 9(b) shows oblivious performance plotted against erraticity and $R^2 = 0.00005$, which is essentially negligible. Oblivious performance does not make dynamic adjustments for demand and so no correlation is expected.

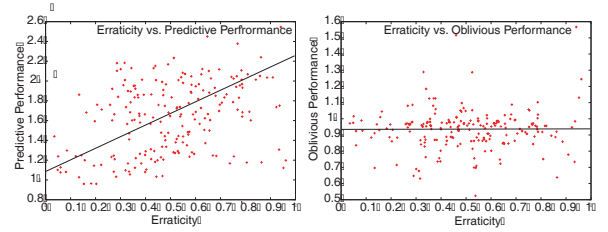


Fig. 9. (a) Erraticity vs. ($\frac{\theta_{PR}}{\theta_{SPR}}$) (b) Erraticity vs. ($\frac{\theta_{OBR}}{\theta_{SPR}}$)

VI. RELATED WORK

We evaluate and highlight our original contributions in light of previous related work.

The problem of wireless mesh network routing, channel assignment, and the joint solution of these two has been extensively studied in the existing literature. For example, routing algorithms are proposed to improve the throughput for wireless mesh networks via integrating MAC layer information [4], such as expected packet transmission time [3], channel cost metric (CCM) which is the sum of expected transmission time weighted by the channel utilization [6]. Joint solutions for channel allocation and routing are explored in [21] using a centralized algorithm and in [5] in a distributed fashion. These heuristic solutions are designed to adapt to the dynamic network condition. However, they lack the theoretical foundation to analyze how well the network performs globally (*e.g.*, whether the network resource is fully utilized, whether the flows share the network in a fair fashion) under their routing schemes.

There are also theoretical studies that formulate these network planning decisions into optimization problems. For example, the works of [7], [22] study the optimal solution of joint channel assignment and routing for maximum throughput

under a multi-commodity flow problem formulation and solves it via linear programming. The work of [8] presents bandwidth allocation schemes to achieve maximum throughput and lexicographical max-min fairness respectively. Further, the work of [23] presents a rate limiting scheme to enforce the fairness among different local access points. These results provide valuable analytical insights to the mesh network design under ideal assumptions such as known static traffic input. However, they may be unsuitable for practical use under highly dynamic traffic situation. Different from these existing works, our work explicitly incorporates traffic behavior analysis and prediction into the routing optimization, thus better fits the routing need in the dynamic wireless mesh networks.

Oblivious routing [24] is a well-studied problem for traffic engineering on the Internet, but has not been extended to interference sets in wireless networks. A polynomially bounded routing is proven to exist within a network in [25]. In [24], a constructive oblivious routing algorithm is given which uses an iterative linear programming model. A single LP formulation, [20] has made oblivious routing practical for the Internet.

Trace analysis has been used to study the behavior of wireless networks in many recent works. For example, [9] statistically characterizes both static flows and roaming flows in a large campus wireless network.

Our work is also related to dynamic traffic engineering [16] in the Internet, which also consider the impact of demand uncertainty in make routing decisions. The major difference between our work and these existing works lies in the different network and traffic models of wireless mesh network and Internet.

VII. CONCLUSION

This paper studies optimal routing strategies for wireless mesh networks with attention to traffic demand uncertainty over time and provable robustness. A predictive algorithm is used providing adaption to traffic dynamics and an oblivious algorithm is tested which offers provable worst-case bounds. We find that the oblivious algorithm is competitive and often outperforms the predictive algorithm, depending in part on the erraticity of the demand. The results show that the problem formulation and choice of deployment algorithm can and must account for traffic demand dynamics.

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